time_series

December 24, 2024

[20]:
```
from sklearn.preprocessing import MinMaxScaler
from sklearn.model_selection import TimeSeriesSplit
from sklearn.model_selection import train_test_split
from sklearn.svm import SVR
from sklearn.metrics import mean_squared_error,␣
↪root_mean_squared_error,mean_absolute_error,r2_score,mean_absolute_percentage_error
import tensorflow as tf
from keras.models import Sequential
from keras.layers import Dense
from keras.layers import LSTM
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
```

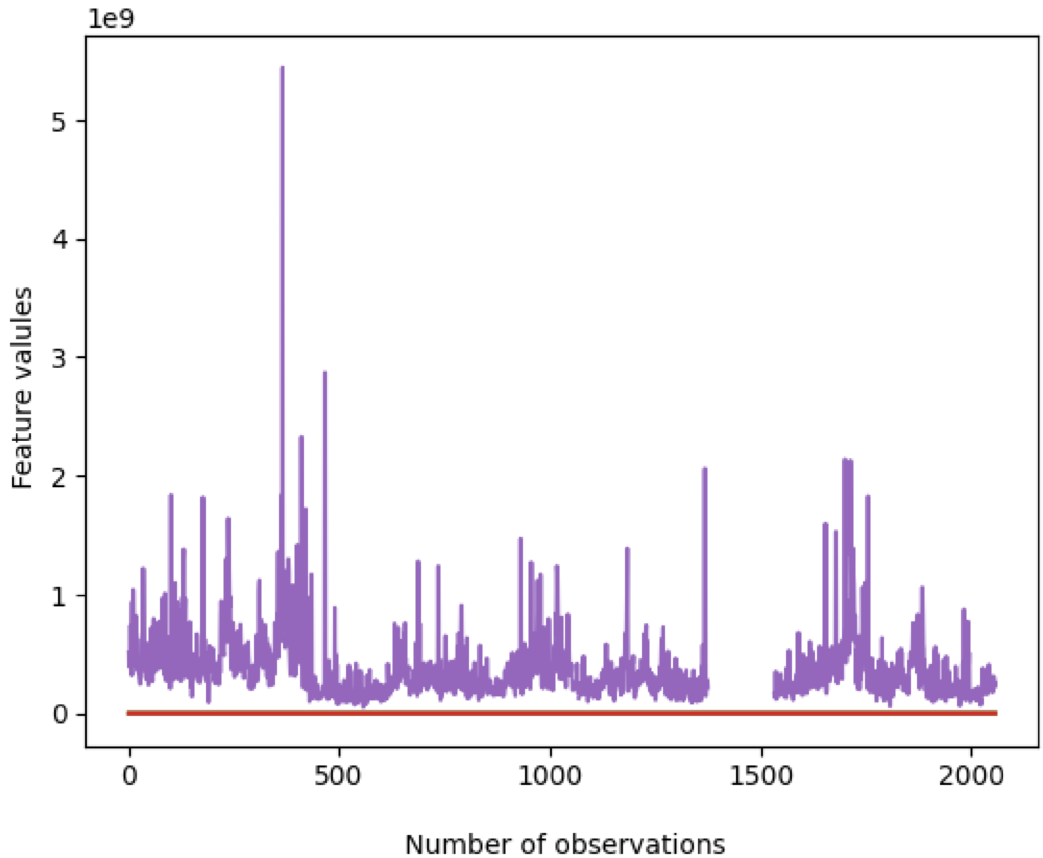
[21]:
```
"""# Reading the required files"""

data = pd.read_csv('NSE(3).csv')


data['Vol.'] = data['Vol.'].replace({'M': '*1e6', 'B': '*1e9'}, regex=True)

# Replace NaN with a placeholder (e.g., np.nan) before applying eval
data['Vol.'] = data['Vol.'].map(lambda x: pd.eval(x) if pd.notna(x) else np.
↪nan).astype(float)

# Display cleaned data
print(data.head())

data.shape
```

```
         Date      Close       Open       High        Low         Vol.  \
0  20-12-2024  101129.09  101247.53  101350.47  100796.84  513560000.0
1  19-12-2024  101248.02  100482.73  101290.57  100482.73  400440000.0
2  18-12-2024  100477.46  100050.94  100477.46  100050.94  389700000.0
3  17-12-2024  100050.94   99927.85  100086.21   99791.29  477880000.0
4  16-12-2024   99922.63   99389.34  100086.80   99389.15  740890000.0

  Change %
```

```
0   -0.12%
1    0.77%
2    0.43%
3    0.13%
4    0.55%
```

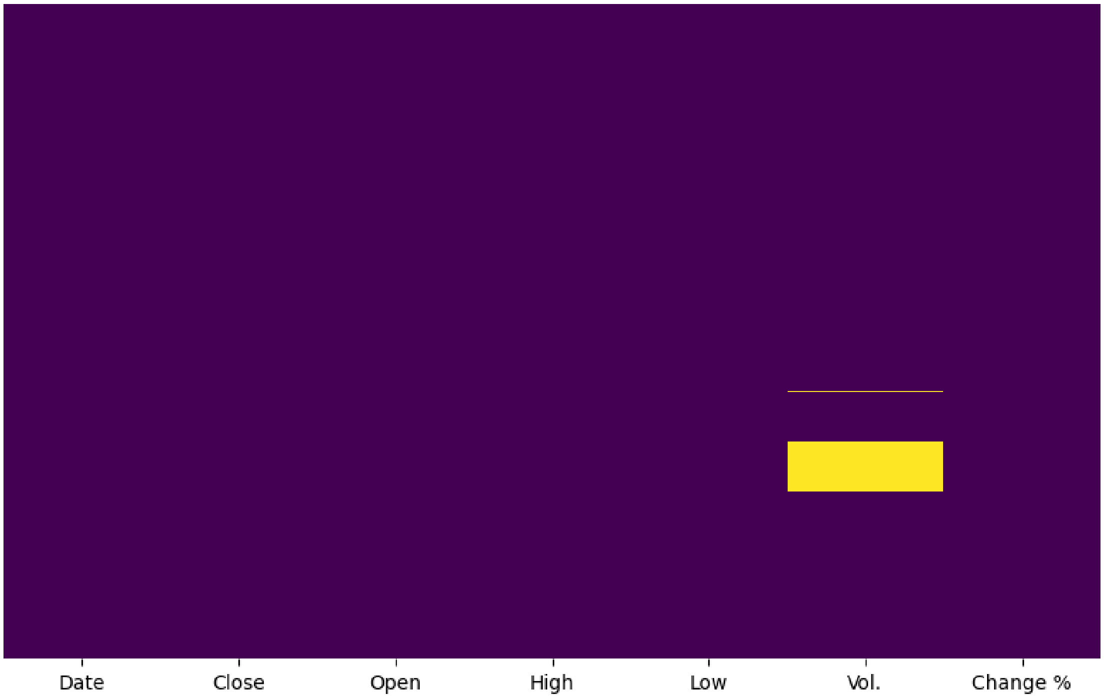
[21]: (2059, 7)

[22]:
```
# Non-Stationary TimeSeries test using visualization
aaa=['Open', 'High', 'Low', 'Close', 'Vol.']
plt.plot(data[aaa])
plt.xlabel('\n Number of observations')
plt.ylabel('\n Feature valules')
plt.show()
```



[23]:
```
import seaborn as sns
import matplotlib.pyplot as plt

# Visualize missing data as a heatmap
plt.figure(figsize=(10, 6))
```

```
sns.heatmap(data.isna(), cbar=False, cmap='viridis', yticklabels=False)
plt.show()
```



[24]:
```
missing_percentage = (data.isna().sum() / len(data)) * 100
print(missing_percentage)
```

```
Date        0.000000
Close       0.000000
Open        0.000000
High        0.000000
Low         0.000000
Vol.        7.916464
Change %    0.000000
dtype: float64
```

[25]:
```
data['Vol.'] = data['Vol.'].interpolate(method='linear')
```

[26]:
```
missing_percentage = (data.isna().sum() / len(data)) * 100
print(missing_percentage)
```

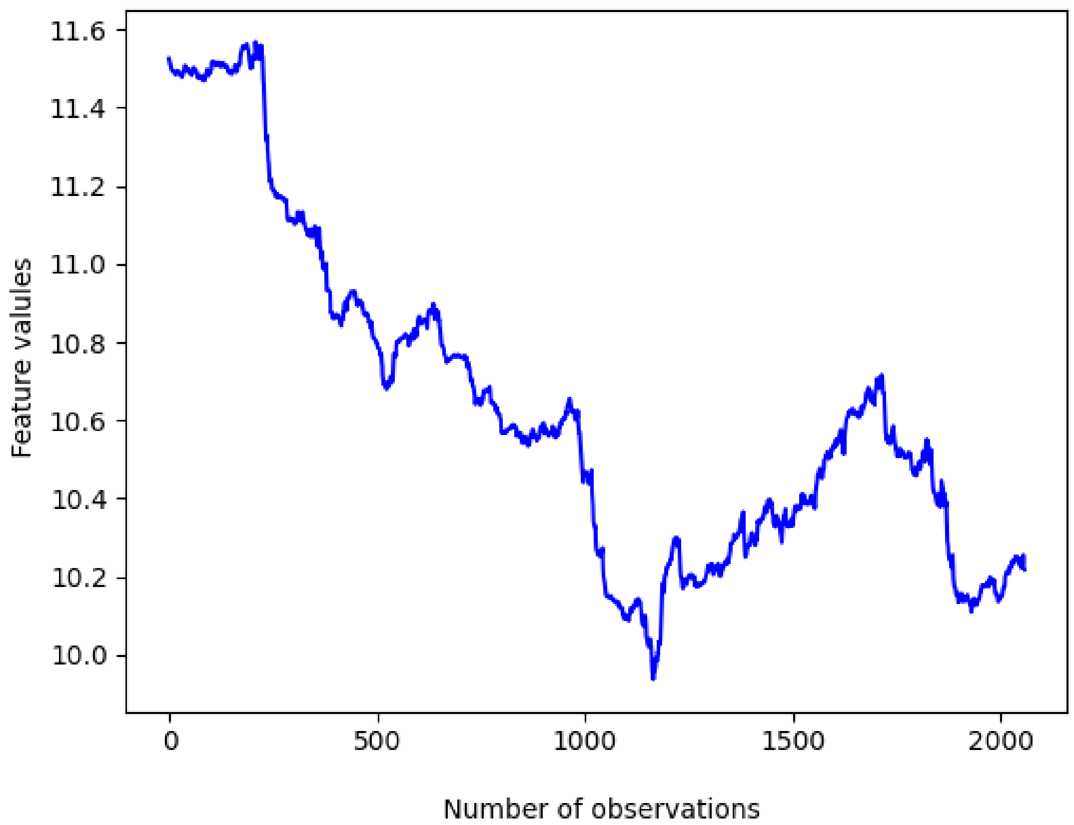
```
Date        0.0
Close       0.0
Open        0.0
High        0.0
Low         0.0
```

```
Vol.         0.0
Change %     0.0
dtype: float64
```

[27]:
```
X = data.values
split = round(len(X) / 2)
X1, X2 = X[0:split], X[split:]

X1 = pd.DataFrame(X1)
X2 = pd.DataFrame(X2)

X1 = X1.apply(pd.to_numeric, errors='coerce')
X2 = X2.apply(pd.to_numeric, errors='coerce')

mean1, mean2 = X1.mean().mean(), X2.mean().mean()
var1, var2 = X1.var().mean(), X2.var().mean()
print('mean1=%f, mean2=%f' % (mean1, mean2))
print('variance1=%f, variance2=%f' % (var1, var2))
```

```
mean1=80262945.351515, mean2=59894920.077337
variance1=20392842179870416.000000, variance2=9544521366813294.000000
```

[28]:
```
# Stationary TimeSeries test using visualization
numeric_data = data.select_dtypes(include=[np.number])
log_data = np.log(numeric_data)
plt.plot(log_data['Open'], 'b')
plt.xlabel('\n Number of observations')
plt.ylabel('\n Feature valulues')
plt.show()

log_data = log_data.replace([np.inf, -np.inf], np.nan)
log_data = log_data.fillna(log_data.mean())
```



[29]:
```
# Stationary Test using Summary Statistics
X = log_data.values
X = np.log(X)
split = round(len(X) / 2)
X1, X2 = X[0:split], X[split:]
mean1, mean2 = X1.mean(), X2.mean()
var1, var2 = X1.var(), X2.var()
print('mean1=%f, mean2=%f' % (mean1, mean2))
print('variance1=%f, variance2=%f' % (var1, var2))
Target_data = log_data['Close']
Train_data = log_data.drop(labels=['Close'], axis=1)


Target_data.head()

MinMax_Scaler = MinMaxScaler()
MinMax_feature_transform = MinMax_Scaler.fit_transform(Train_data)
MinMax_feature_transform = pd.DataFrame(MinMax_feature_transform,␣
 ↪columns=Train_data.columns, index=Train_data.index)
scaled_target = MinMax_Scaler.fit_transform(Target_data.values.reshape(-1, 1))
```

```
scaled_features_df = pd.DataFrame(MinMax_feature_transform, columns=Train_data.
 ↪columns, index=Train_data.index)
```

```
mean1=2.509269, mean2=2.459700
variance1=0.055445, variance2=0.063715
```

[30]:
```
# Define a function to create input-output sequences for sliding window
def create_sequences(scaled_target, window_size):
    X, y = [], []
    for i in range(len(scaled_target) - window_size):
        X.append(scaled_target[i:i + window_size])  # Input: window_size time␣
 ↪steps
        y.append(scaled_target[i + window_size])    # Output: the next time step
    return np.array(X), np.array(y)

# Apply sliding window
window_size = 60
X, y = create_sequences(scaled_target, window_size)
```

[31]:
```
# Split the data
timesplit= TimeSeriesSplit(n_splits=10)
for train_index, test_index in timesplit.split(MinMax_feature_transform):
        X_train, X_test = MinMax_feature_transform[:len(train_index)],␣
 ↪MinMax_feature_transform[len(train_index):␣
 ↪(len(train_index)+len(test_index))]
        y_train, y_test = Target_data[:len(train_index)].values.ravel(),␣
 ↪Target_data[len(train_index): (len(train_index)+len(test_index))].values.
 ↪ravel()
```

[32]:
```
"""# LSTM"""

# fix random seed for reproducibility
tf.random.set_seed(7)

print(X_train.shape, X_test.shape, y_train.shape, y_test.shape)

#Process the data for LSTM
trainX =np.array(X_train)
testX =np.array(X_test)
X_train = trainX.reshape(X_train.shape[0], 1, X_train.shape[1])
X_test = testX.reshape(X_test.shape[0], 1, X_test.shape[1])

trainY =np.array(y_train)
```

```
(1872, 4) (187, 4) (1872,) (187,)
```

[33]:
```
#Building the LSTM Model
model = Sequential()
```

```
model.add(LSTM(units=50, input_shape=(1, trainX.shape[1]), activation='relu',␣
↪return_sequences=False))
#model.add(LSTM(units=50, dropout=0.2, input_shape=(1, trainX.shape[1]),␣
↪activation='relu', return_sequences=False))
model.add(Dense(1))
model.compile(loss='mean_squared_error', optimizer='adamax')

history = model.fit(X_train, y_train, epochs=100, batch_size=1)

lstm_prediction = model.predict(X_test)
print(len(lstm_prediction))
```

```
c:\Users\a\Desktop\projects\LSTM\japan\venv\Lib\site-
packages\keras\src\layers\rnn\rnn.py:200: UserWarning: Do not pass an
`input_shape`/`input_dim` argument to a layer. When using Sequential models,
prefer using an `Input(shape)` object as the first layer in the model instead.
  super().__init__(**kwargs)
```

```
Epoch 1/100
1872/1872          4s 1ms/step -
loss: 67.3389
Epoch 2/100
1872/1872          3s 1ms/step -
loss: 4.0983
Epoch 3/100
1872/1872          3s 1ms/step -
loss: 1.0387
Epoch 4/100
1872/1872          3s 1ms/step -
loss: 0.2732
Epoch 5/100
1872/1872          2s 1ms/step -
loss: 0.1690
Epoch 6/100
1872/1872          2s 1ms/step -
loss: 0.1034
Epoch 7/100
1872/1872          2s 1ms/step -
loss: 0.0528
Epoch 8/100
1872/1872          2s 1ms/step -
loss: 0.0194
Epoch 9/100
1872/1872          2s 1ms/step -
loss: 0.0040
Epoch 10/100
1872/1872          2s 1ms/step -
loss: 0.0011
```

```
Epoch 11/100
1872/1872            3s 1ms/step -
loss: 4.7119e-04
Epoch 12/100
1872/1872            2s 1ms/step -
loss: 2.0539e-04
Epoch 13/100
1872/1872            3s 1ms/step -
loss: 1.3706e-04
Epoch 14/100
1872/1872            3s 1ms/step -
loss: 1.2174e-04
Epoch 15/100
1872/1872            2s 1ms/step -
loss: 1.1258e-04
Epoch 16/100
1872/1872            3s 1ms/step -
loss: 1.0626e-04
Epoch 17/100
1872/1872            3s 1ms/step -
loss: 1.0186e-04
Epoch 18/100
1872/1872            3s 1ms/step -
loss: 9.8109e-05
Epoch 19/100
1872/1872            3s 1ms/step -
loss: 9.5758e-05
Epoch 20/100
1872/1872            2s 1ms/step -
loss: 9.3420e-05
Epoch 21/100
1872/1872            3s 1ms/step -
loss: 9.0381e-05
Epoch 22/100
1872/1872            2s 1ms/step -
loss: 8.6505e-05
Epoch 23/100
1872/1872            2s 1ms/step -
loss: 8.3809e-05
Epoch 24/100
1872/1872            2s 1ms/step -
loss: 8.1529e-05
Epoch 25/100
1872/1872            3s 1ms/step -
loss: 8.0343e-05
Epoch 26/100
1872/1872            3s 1ms/step -
loss: 7.9098e-05
```

```
Epoch 27/100
1872/1872             2s 1ms/step -
loss: 7.7672e-05
Epoch 28/100
1872/1872             3s 1ms/step -
loss: 7.5269e-05
Epoch 29/100
1872/1872             3s 1ms/step -
loss: 7.3875e-05
Epoch 30/100
1872/1872             3s 1ms/step -
loss: 7.3502e-05
Epoch 31/100
1872/1872             3s 1ms/step -
loss: 7.3828e-05
Epoch 32/100
1872/1872             3s 1ms/step -
loss: 7.4045e-05
Epoch 33/100
1872/1872             3s 1ms/step -
loss: 7.3168e-05
Epoch 34/100
1872/1872             3s 1ms/step -
loss: 7.2176e-05
Epoch 35/100
1872/1872             3s 1ms/step -
loss: 7.1477e-05
Epoch 36/100
1872/1872             3s 1ms/step -
loss: 7.0290e-05
Epoch 37/100
1872/1872             2s 1ms/step -
loss: 6.9707e-05
Epoch 38/100
1872/1872             3s 1ms/step -
loss: 6.8847e-05
Epoch 39/100
1872/1872             3s 1ms/step -
loss: 6.7696e-05
Epoch 40/100
1872/1872             3s 1ms/step -
loss: 6.6866e-05
Epoch 41/100
1872/1872             3s 1ms/step -
loss: 6.6085e-05
Epoch 42/100
1872/1872             3s 1ms/step -
loss: 6.5116e-05
```

```
Epoch 43/100
1872/1872            3s 1ms/step -
loss: 6.4129e-05
Epoch 44/100
1872/1872            2s 1ms/step -
loss: 6.3449e-05
Epoch 45/100
1872/1872            3s 1ms/step -
loss: 6.2836e-05
Epoch 46/100
1872/1872            3s 2ms/step -
loss: 6.2285e-05
Epoch 47/100
1872/1872            3s 1ms/step -
loss: 6.1764e-05
Epoch 48/100
1872/1872            3s 1ms/step -
loss: 6.1210e-05
Epoch 49/100
1872/1872            2s 1ms/step -
loss: 6.0761e-05
Epoch 50/100
1872/1872            3s 1ms/step -
loss: 6.0326e-05
Epoch 51/100
1872/1872            2s 1ms/step -
loss: 5.9944e-05
Epoch 52/100
1872/1872            3s 1ms/step -
loss: 5.9652e-05
Epoch 53/100
1872/1872            3s 1ms/step -
loss: 5.9373e-05
Epoch 54/100
1872/1872            3s 1ms/step -
loss: 5.9065e-05
Epoch 55/100
1872/1872            2s 1ms/step -
loss: 5.8781e-05
Epoch 56/100
1872/1872            2s 1ms/step -
loss: 5.8547e-05
Epoch 57/100
1872/1872            2s 1ms/step -
loss: 5.8403e-05
Epoch 58/100
1872/1872            3s 1ms/step -
loss: 5.8063e-05
```

```
Epoch 59/100
1872/1872               2s 1ms/step -
loss: 5.7813e-05
Epoch 60/100
1872/1872               3s 2ms/step -
loss: 5.7538e-05
Epoch 61/100
1872/1872               3s 2ms/step -
loss: 5.7263e-05
Epoch 62/100
1872/1872               3s 2ms/step -
loss: 5.6991e-05
Epoch 63/100
1872/1872               3s 2ms/step -
loss: 5.6690e-05
Epoch 64/100
1872/1872               3s 1ms/step -
loss: 5.6409e-05
Epoch 65/100
1872/1872               2s 1ms/step -
loss: 5.6129e-05
Epoch 66/100
1872/1872               3s 1ms/step -
loss: 5.5861e-05
Epoch 67/100
1872/1872               3s 1ms/step -
loss: 5.5588e-05
Epoch 68/100
1872/1872               3s 1ms/step -
loss: 5.5319e-05
Epoch 69/100
1872/1872               3s 1ms/step -
loss: 5.5024e-05
Epoch 70/100
1872/1872               3s 1ms/step -
loss: 5.4709e-05
Epoch 71/100
1872/1872               3s 1ms/step -
loss: 5.4413e-05
Epoch 72/100
1872/1872               3s 1ms/step -
loss: 5.4111e-05
Epoch 73/100
1872/1872               3s 1ms/step -
loss: 5.3812e-05
Epoch 74/100
1872/1872               2s 1ms/step -
loss: 5.3531e-05
```

```
Epoch 75/100
1872/1872           3s 1ms/step -
loss: 5.3253e-05
Epoch 76/100
1872/1872           3s 1ms/step -
loss: 5.2976e-05
Epoch 77/100
1872/1872           3s 1ms/step -
loss: 5.2743e-05
Epoch 78/100
1872/1872           3s 1ms/step -
loss: 5.2461e-05
Epoch 79/100
1872/1872           3s 1ms/step -
loss: 5.2176e-05
Epoch 80/100
1872/1872           3s 2ms/step -
loss: 5.1879e-05
Epoch 81/100
1872/1872           3s 1ms/step -
loss: 5.1585e-05
Epoch 82/100
1872/1872           3s 2ms/step -
loss: 5.1297e-05
Epoch 83/100
1872/1872           2s 1ms/step -
loss: 5.1032e-05
Epoch 84/100
1872/1872           3s 1ms/step -
loss: 5.0676e-05
Epoch 85/100
1872/1872           3s 1ms/step -
loss: 5.0413e-05
Epoch 86/100
1872/1872           3s 1ms/step -
loss: 5.0126e-05
Epoch 87/100
1872/1872           3s 1ms/step -
loss: 4.9676e-05
Epoch 88/100
1872/1872           3s 1ms/step -
loss: 4.9353e-05
Epoch 89/100
1872/1872           3s 1ms/step -
loss: 4.8993e-05
Epoch 90/100
1872/1872           3s 2ms/step -
loss: 4.8651e-05
```

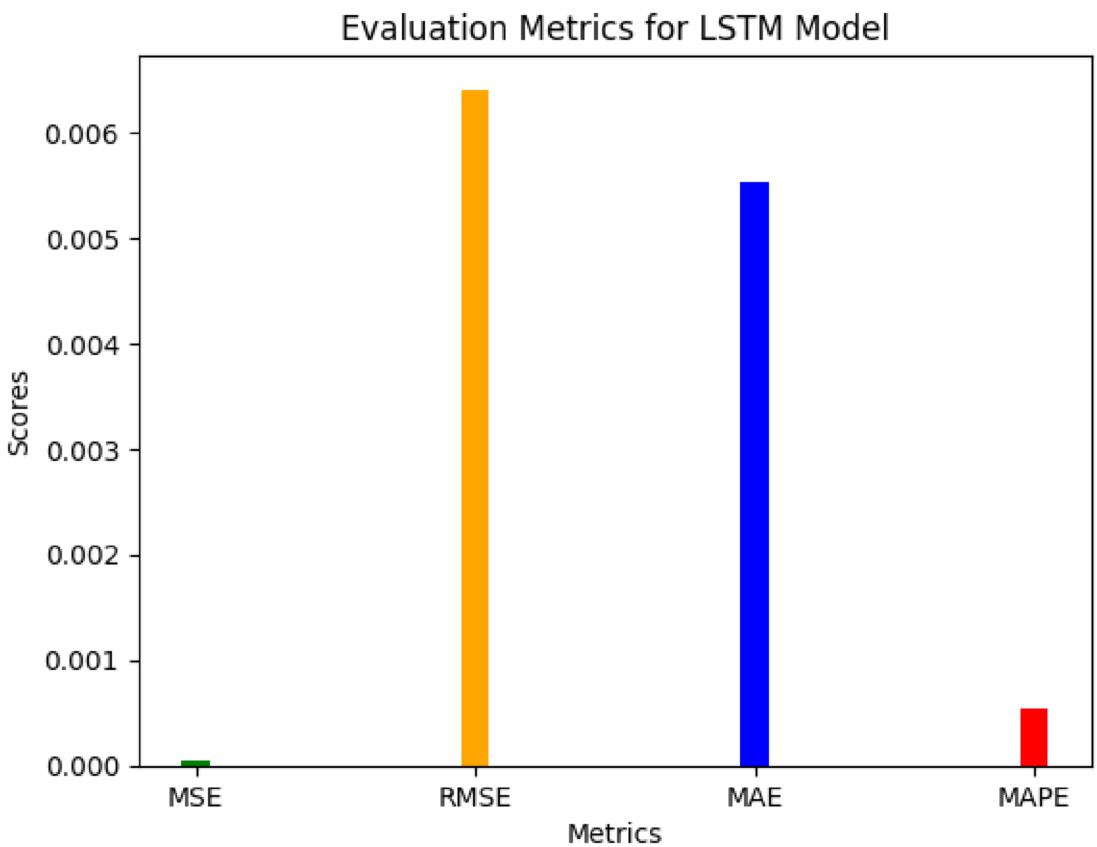
```
Epoch 91/100
1872/1872            3s 2ms/step -
loss: 4.8535e-05
Epoch 92/100
1872/1872            3s 1ms/step -
loss: 4.8214e-05
Epoch 93/100
1872/1872            2s 1ms/step -
loss: 4.7913e-05
Epoch 94/100
1872/1872            3s 2ms/step -
loss: 4.7658e-05
Epoch 95/100
1872/1872            3s 1ms/step -
loss: 4.7453e-05
Epoch 96/100
1872/1872            3s 2ms/step -
loss: 4.7033e-05
Epoch 97/100
1872/1872            3s 2ms/step -
loss: 4.6862e-05
Epoch 98/100
1872/1872            3s 1ms/step -
loss: 4.6696e-05
Epoch 99/100
1872/1872            3s 2ms/step -
loss: 4.6507e-05
Epoch 100/100
1872/1872            3s 1ms/step -
loss: 4.6244e-05
6/6          0s 38ms/step
187
```

[34]:

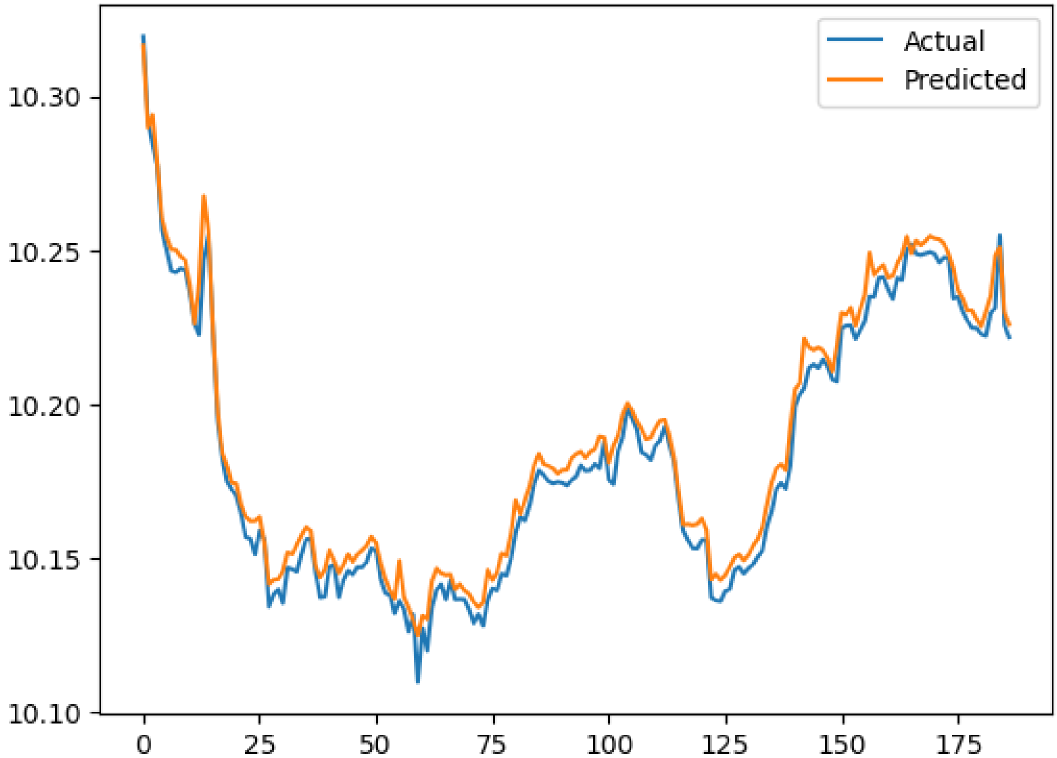
```
MSE = round(mean_squared_error(y_test, lstm_prediction), 9)
RMSE = round(np.sqrt(MSE), 9)
MAE = round(mean_absolute_error(y_test, lstm_prediction), 9)
MAPE=round(mean_absolute_percentage_error(y_test, lstm_prediction), 9)
print('MSE: ', MSE)
print('RMSE: ', RMSE)
print('MAE', MAE)
print('MAPE', MAPE)

x = [0, 1, 2, 3]
plt.bar(x[0], MSE, width=0.1, color='GREEN', label='MSE')
plt.bar(x[1], RMSE, width=0.1, color='orange', label='RMSE')
plt.bar(x[2], MAE, width=0.1, color='blue', label='MAE')
plt.bar(x[3], MAPE, width=0.1, color='RED', label='MAPE')
```

```
plt.xticks(x, ['MSE', 'RMSE', 'MAE','MAPE'])
plt.xlabel("Metrics")
plt.ylabel("Scores")
plt.title("Evaluation Metrics for LSTM Model")
plt.show()
```

```
MSE:  4.0998e-05
RMSE:  0.006402968
MAE 0.005528818
MAPE 0.000543057
```



[35]:
```
plt.plot(y_test, label='Actual')
plt.plot(lstm_prediction, label='Predicted')
plt.legend()
plt.show()
```


Actual
Predicted
10.30
10.25
10.20
10.15
10.10
0
25
50
75
100
125
150
175